Journal of Business Research 177 (2024) 114637

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Gliding from regenerative unlearning toward digital transformation via collaboration with customers and organisational agility

Clara Cubillas-Para[a,*], Juan Gabriel Cegarra-Navarro[a], Elena-Mădălina Vătămănescu[b]

[a] *Business Faculty, Technical University of Cartagena, Cartagena, Spain*

[b] *Faculty of Management, National University of Political Studies and Public Administration (S.N.S.P.A), Bucharest, Romania*

ARTICLE INFO

Keywords:
Digital transformation
Organizational agility
Collaboration with customers
Regenerative unlearning

ABSTRACT

The digital evolution that businesses are facing highlights the need for organisations to be agile, to collaborate with customers and to change the mindset of employees and managers to achieve effective digital transformation. This study explores the role of regenerative unlearning, defined as a dynamic capability that enables organisations to adapt by systematically renewing knowledge structures, in customer collaboration, organisational agility and digital transformation. Using PLS-SEM, a sample of medium-sized Spanish manufacturing companies was analysed. The results show that regenerative unlearning improves customer collaboration, organisational agility, and digital transformation. Findings also show the influence of customer collaboration on organisational agility and of organisational agility on digital transformation. This research contributes to the literature by providing a better understanding of the importance of regenerative unlearning, collaboration with customers and agility in the digital context of the Spanish manufacturing industry.

1. Introduction

Digitalisation is considered the main driver of global economic expansion (Guo, Yin, & Liu, 2023). Organisations, compelled by the dynamic nature of their operational environments, have embraced digital transformation initiatives to adapt to the change, managing the inherent uncertainties related to them (Statsenko & Corral de Zubielqui, 2020). In fact, the Covid-19 pandemic (Fahey & Hino, 2020) or the need to meet the challenges of sustainable growth (Broccardo, Zicari, Jabeen, & Bhatti, 2023) have shown the organisational importance of embracing digital transformation processes. Indeed, in the literature on strategic management, digital transformation has drawn particular interest (Vuchkovski, Zalaznik, Mitręga, & Pfajfar, 2023) as it is considered a strategic response to technological and market changes (Caputo, Pizzi, Pellegrini, & Dabić, 2021). Therefore, digital transformation has emerged as a way for organisations to face their environment dynamism while meeting their stakeholders' needs with intelligent and interconnected digital services (Çıdık, Boyd, & Thurairajah, 2017; Hamid, 2022).

The integration of digital technologies has led to disruptive changes in organisations (Wang, Liu, Li, & Lei, 2023). Indeed, it involves processes that redefine and enhance existing techniques and customer experiences, needing a collective effort from internal and external stakeholders (Çebi, Özdemir, Reisoğlu, & Çolak, 2022; Çıdık et al., 2017). This, in turn, triggers the readjustment of internal and external knowledge (Vătămănescu et al., 2018, 2020, 2023a, 2023b). Digital transformation entails changing how a company uses digital technologies to create a new business model that generates greater value than the previous one (Verhoef et al., 2021). This requires the adoption of new knowledge structures both inside and outside the organisation to achieve the intended strategic objectives (Li et al., 2023). Furthermore, organisations integrating digital technologies must update knowledge, routines, and behaviour to prevent inertia and enhance flexibility (Wang et al., 2023). Consequently, the capacity to challenge old mental models, change routines, and relearn – known as unlearning – appears crucial in digital transformation processes (Cegarra-Navarro & Wensley, 2019).

In this study we contend that when the effort of regenerating knowledge is not individual but collective, a new capability arises, referring to it as "regenerative unlearning". We define regenerative unlearning as the organisational dynamic capability to replace or update obsolete mental models, routines, and knowledge structures from a collective point of view. To the best of our knowledge, no previous studies have addressed the role of regenerative unlearning in digital transformation processes. However, intentional unlearning has been

* Corresponding author.
E-mail addresses: Clara.cubillas@upct.es (C. Cubillas-Para), Juan.cegarra@upct.es (J.G. Cegarra-Navarro).

https://doi.org/10.1016/j.jbusres.2024.114637
Received 6 June 2023; Received in revised form 21 March 2024; Accepted 23 March 2024
Available online 27 March 2024
0148-2963/

found to positively influence digital process innovation (Wang et al., 2023). Therefore, this study aims to tackle this gap, arguing that when organisations undergo digital transformation processes, there is a collective need to regenerate knowledge, routines, and behaviours.

A successful digital transformation process may also require the organisational capability to master change, known as organisational agility (Cegarra-Navarro et al., 2016). In fact, previous studies have found relevant correlations between digitalisation and agility, which are strong antecedents of firms' flexibility to deal with unexpected changes and drive innovation (Niewohner et al., 2019). Organisational agility seeks to address changes in customers' needs (Mehdibeigi, Dehghani, & Yaghoubi, N.m. , 2016) and can be improved by customer-oriented experiences (Mihardjo, Sasmoko, Alamsjah, & Djap, 2019). In studies about digital technologies, agility has proven to help organisations increase their adaptability to technologies (Guo et al., 2023). However, to the best of our knowledge, no studies to date have analysed organisational agility's role in digital transformation processes. Thus, this study aims to fill this gap by analysing the effect of organisational agility on digital transformation processes.

Based on the above, our research questions are (1) Does regenerative unlearning influence customer collaboration, organisational agility, and digital transformation? and (2) Does customer collaboration affect organisational agility, which in turn affects digital transformation? We have analysed a sample of medium-sized manufacturing companies in Spain to answer these questions. The study's results, assessed using SmartPLS software, confirmed the suggested relationships. Findings reveal that regenerative unlearning enhances customer collaboration and organisational agility, thereby improving digital transformation processes. This involves eliminating unnecessary, outdated, or incorrect routines by productively and innovatively regenerating them. These findings underscore the significance of regenerating knowledge and practices when embracing and implementing digital transformation. Similarly, they demonstrate that customer collaboration positively influences organisational agility, positively impacting digital transformation processes. These results highlight the role of knowledge regeneration in successful digital transformation processes.

2. Conceptual framework

Businesses are experiencing rapid changes due to the digital revolution, which has, in turn, opened a wealth of possibilities for entrepreneurs to enhance their companies using digital technologies (Feliciano-Cestero, Ameen, Kotabe, Paul, & Signoret, 2023). Defined as a combination of information, computing, communication, and connectivity technologies, digital technologies are instrumental in transforming various aspects of business, including strategies, processes, capabilities, products, and services (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013). Verhoef et al. (2021) identify three phases in which organisations can apply digital technologies to promote digital change: The first, *digitisation*, involves transitioning from analogue to digital information formats; The second phase, called *digitalisation*, refers to the ways in which digital technologies can be used to alter existing business processes; Finally, the last phase, termed *digital transformation*, involves enterprise-wide change leading to a new business model.

Digital transformation is the most significant and disruptive digital change brought about by digital technologies, resulting in a continuous improvement process that integrates these technologies into all company areas (Garcia-Perez, Cegarra-Navarro, Sallos, Martinez-Caro, & Chinnaswamy, 2022; Li et al., 2023) and causing substantial organisational changes (Vial, 2019). Verhoef et al. (2021,p. 889) define digital transformation as "*a change in how a firm employs digital technologies, to develop a new digital business model that helps to create and appropriate more value for the firm*". Thus, the digital transformation process results in the optimisation of organisations' operations, which allows them to use their resources better and obtain competitive advantages (Fenech, Baguant, & Ivanov, 2019) and major business gains (Vuchkovski et al., 2023). In this regard, organisations that invest in digital transformation will be prepared for future scenarios and ready to survive the challenges of the market (Li et al., 2023).

Digital transformation, however, is not an effortless process to implement (Jones, Hutcheson, & Camba, 2021). Among the main barriers found in the literature to it are a lack of skills and experience, an immature digital culture, a lack of budgets and resources, data privacy and security concerns, a lack of economic growth, and a lack of ability to properly interpret data (Jones et al., 2021). In fact, companies have faced significant challenges due to the progression of digital technologies and the rapid growth of digital enterprises, such as the impact on retail companies caused by the expansion of Amazon, and on hotel companies affected by the presence of Airbnb and Booking.com (Verhoef et al., 2021). Therefore, companies should overcome these barriers and adapt to the changing environment, which implies an organisational transformation focused primarily on people (Chan, Okumus, & Chan, 2015; Filieri, 2010; McDermott & O'Dell, 2001). The foregoing challenges show the need for companies to avoid inertia and achieve rapid change to enable the digital transition (Wang et al., 2023). In this sense, in the process towards digital transformation, organisations must question the usefulness or validity of their intangible resources such as organisational knowledge (Mattila, Yrjölä, & Hautamäki, 2021). The organisational capability to update knowledge, learn from mistakes and think outside the box has been reported to allow organisations to adapt better and faster to new situations (Zhao, Lu, & Wang, 2013; Vătămănescu, Andrei, Gazzola, & Dominici, 2018; Vătămănescu, Cegarra-Navarro, Andrei, Dincă, & Alexandru, 2020). This capacity is known as intentional unlearning and requires the organisational ability to enable employee engagement in generating ideas, seizing opportunities, and proposing change-oriented strategies (Cubillas-Para, Cegarra-Navarro, & Wensley, 2023).

A dynamic capability implies that not only an individual but also the organisation can adapt, integrate, and reconfigure its resources and capabilities in response to changing environmental conditions (Pavlou & El Sawy, 2011; Teece, 2007; Teece & Pisano, 1994). Under this framework, when an organisation faces a change, some individuals may need to unlearn to occupy new positions or perform tasks different from those they have been performing. In this study, we introduce an evolution of the concept of intentional unlearning, termed "regenerative unlearning". With this new concept, we recognise the imperative of collective organisational change during digital transformation. We define regenerative unlearning as the organisational and collective dynamic capability to intentionally update mental models, alter routines and engage in relearning processes to respond skilfully to changes in the environment of the organisation. Therefore, regenerative unlearning is a dynamic capability that helps organisations to adapt to its volatile environment by regenerating and reconstructing the knowledge structures which need to change (Zheng, Zhang, & Du, 2011).

2.1. Regenerative unlearning: Impact on collaboration with customers, organisational agility and digital transformation

Organisations must be able to leverage not only internal dynamic capabilities but also external interactions (Statsenko & Corral de Zubielqui, 2020; Vătămănescu et al., 2023a, 2023b) to develop digital strategies in response to market changes. Digital strategies seek to leverage digital resources to create value within organisations by including digital resources in functional areas (Bharadwaj et al., 2013). In this regard, digital transformation strategies are focused on use of technologies, changes in value creation, structural changes, and financial aspects (Matt, Hess, & Benlian, 2015). When developing their digital transformation strategies, organisations must ensure that their supply responds to the ever-more complexity of customer needs (Heirati, O'Cass, Schoefer, & Siahtiri, 2016).

Increasingly, organisations use external knowledge, especially consumer knowledge, in times of rapidly changing market conditions to better understand their customers' needs and strengthen their internal knowledge pools (Kindermann, Schmidt, Burger, & Flatten, 2022). Indeed, organisational success depends on its ability to exploit customer knowledge and transform it into innovations (Statsenko & Corral de Zubielqui, 2020). Several concepts have been set out and tested by academics to envision the inclusion of customers in corporate innovation initiatives (i.e., customer involvement) (Kindermann et al., 2022; Najafi-Tavani, Zaefarian, Robson, Naudé, & Abbasi, 2022), customer participation (Morgan & Anokhin, 2023) or customer collaboration (Heirati et al., 2016). However, a clear definition of these terms is lacking, as they may refer to customers either as information sources or as co-developers of new products or services (Kindermann et al., 2022).

Bearing this in mind, in this study, we define collaboration with customers as the co-creation strategic actions adopted by companies to add value not only to their organisational resources but also to their relationship with customers. To be effective, this relationship must be based on trust, information sharing, and collaborative issue resolution (McEvily & Marcus, 2005; Statsenko & Corral de Zubielqui, 2020). As a result of firm-customer collaboration, organisations will benefit from new insights, capital, knowledge, and capabilities (Morgan & Anokhin, 2023) that will allow them to maintain their competitive advantage in situations where a change is needed (Heirati et al., 2016).

When it comes to innovative efforts within organisations, such as the creation of new products or services or the development of innovative processes, where collaboration with customers is very important, knowledge updating is crucial (Ortega-Gutiérrez, Cepeda-Carrión, & Alves, 2022). Specifically, an adequate unlearning context emerges as paramount (Cegarra-Navarro, Wensley, Batistic, Evans, & Cubillas-Para, 2021). Ortega-Gutiérrez et al. (2022) showed that when companies unlearn, their ability to focus on the customer is greater. In a similar way, literature has revealed that entrepreneurial orientation, based on innovativeness, proactiveness, and risk-taking, influences collaboration with customers (Morgan & Anokhin, 2023; McEvily & Marcus, 2005) as organisations may continually examine the environment for collaborative opportunities, access to external knowledge and avoidance of organisational inertia.

However, there are no studies that have analysed the influence of unlearning on collaboration with customers. In this regard, a company that fosters regenerative unlearning could get access to fresh ideas, which will promote collaboration with customers (Heirati et al., 2016). Indeed, the regeneration of internal knowledge expands and enlarges a firm's external knowledge base, increasing the diversity and heterogeneity of the organisation's external knowledge (Echajari & Thomas, 2015; Tsai, 2018; Yang & Wang, 2017). Drawing from these insights, our first hypothesis posits that the regeneration of organisational knowledge will positively influence customer collaboration.

H1: Regenerative Unlearning has a positive influence on Collaboration with Customers.

Unlearning also allows the organisation to have structures that encourage the participation of all stakeholders and a global vision of the problems of the environment, promoting organisational agility (Tanushree, Sahoo & Chaubey, 2023). In this regard, organisational agility is the organisation's capacity to perceive, adapt and respond to change at the speed required by the context (Walter, 2021). Through organisational agility, it is possible to thrive and grow in an increasingly volatile, uncertain, complex, and ambiguous world (Winby & Worley, 2014). It implies productive meetings and a corporate culture that avoids conflict and fosters consensus to find the best solution to a problem (Tanushree et al., 2023).

Organisational agility requires creating new knowledge (Cegarra-Navarro, Soto-Acosta, & Wensley, 2016; Zain, Rose, Abdullah, & Masrom, 2005), becoming the result of adapting knowledge from one context to another (Pereira, Mellahi, Temouri, Patnaik, & Roohanifar, 2019). Accordingly, organisations must be able to recognise the necessary changes, adapt their routines, recognise divergences, and respond to them through relearning since organisational agility allows organisations to change their structure in response to environmental shifts. Thus, a company capable of regenerating its knowledge can also use novel technology or market-related knowledge and apply it to digital information that other stakeholders can understand. Accordingly, we propose our second hypothesis arguing that by regenerating obsolete practices and knowledge, organisations become more adaptable and responsive to change, improving their agility.

H2: Regenerative Unlearning has a positive influence on Organisational Agility.

Regenerative unlearning is a strategic resource that allows organisations to update and balance knowledge (Cegarra-Navarro & Wensley, 2019). In the context of digital transformation, multifaceted and multilevel knowledge becomes essential (Bican & Brem, 2020; Bordeleau & Felden, 2020; Willie & Nkomo, 2019). This underscores the need for digital transformation initiatives to integrate expertise from different fields (Kane, Palmer, Nguyen, Kiron, & Buckley, 2015). In doing so, regenerative unlearning helps the organisation to update the internal knowledge, as well as the external one. Furthermore, given the rapid evolution of digital technologies, there is frequently considerable uncertainty regarding the foundational assumptions of digital transformation strategies (Matt et al., 2015).

As stated by Matt et al. (2015), digital transformation strategies need continuous reassessment, encompassing an evaluation of both the underlying assumptions and the advancements made in the transformation process. Together with that, a redesign of the mindset of the organisation's employees and managers is also critical to its success in digital transformation (Gimpel et al., 2018). In this context, it may be crucial for all employees of the organisation to regenerate their knowledge, practices, and processes to adapt to modern technologies, procedures, strategies, and business models introduced within the organisation as part of digital transformation. This adaptation will be imperative to achieving the success of the transformation process. Based on the above, we propose our third hypothesis arguing that regenerative unlearning will have a positive influence on digital transformation process.

H3: Regenerative Unlearning has a positive influence on Digital Transformation.

2.2. *Organisational agility, collaboration with customers and digital transformation*

Organisational agility is related to the ability of companies to cope with unexpected changes in the organisation environment and capitalise on new opportunities arising from such changes (Guo et al., 2023). Agile organisations are, therefore, designed to predict and cope with business change to achieve customer and employee satisfaction (Mehdibeigi et al., 2016). Organisational agility can improve by customer-oriented experiences (Mihardjo et al., 2019) given that one of its main goals is to face and solve changes in customer needs (Mehdibeigi et al., 2016). Indeed, as organisations can use customers as co-developers to create value (Kindermann et al., 2022), their knowledge improves organisational agility (Mehdibeigi et al., 2016), enhancing new product speed-to-market (García-Murillo & Annabi, 2002) and organisational innovativeness (Kindermann et al., 2022).

Based on these studies, it is arguable that organisations that collaborate with their customers will improve their organisational agility as they will have a better understanding of the dynamics of market needs. However, to the best of our knowledge, there are no studies that have analysed the influence of customer collaboration on organisational agility. Therefore, we posit that companies that increasingly recognise the importance of collaboration with customers will improve their agility in responding to new needs and market changes. In this sense, we propose our next hypothesis contending that organisational agility, which involves being flexible, adaptable, and able to change strategies to meet customer needs (Mehdibeigi et al., 2016), can be improved by fostering a culture of collaboration with customers.

H4: Collaboration with Customers has a positive influence on Organisational Agility.

Digital transformation is about changing the existing sociotechnical structures, previously mediated by non-digital devices or relationships, into structures that are mediated by digitised tools and relationships with digital skills (Shakina, Parshakov, & Alsufiev, 2021). Therefore, digital transformation involves a series of complex knowledge activities, such as developing design thinking to analyse and enhance the customer journey or implementing automated customer service (McDermott, Foley, Antony, Sony, & Butler, 2022). In this context, the agility necessary to adapt to technological developments may help organisations deliver timely, valuable, structured, and validated knowledge. In fact, previous studies have shown that for innovative performance in digital start-ups, organisational agility is crucial as it helps them acquire the resilience and adaptability necessary to respond to quick changes in the digital marketplace (Guo et al., 2023).

Organisational agility is crucial for being successful in the rapidly changing digital environment (Gimpel & Röglinger, 2015). As organisational agility enables organisational change, digital transformation is also inferred as the consequence of organisational agility. Gimpel et al. (2018) highlighted that organisational agility is critical in the digital transformation of an organisation and should include all aspects of organisational setups such as processes, governance, staff, culture, and information technology. Hence, we propose our last hypothesis, which argues that organisational agility will positively influence digital transformation initiatives.

H5: Organisational Agility has a positive influence on Digital Transformation.

Fig. 1 shows a summary of the proposed model.

3. Methodology

3.1. Data collection

The population for the present study consisted of Spanish manufacturing companies with an average workforce ranging from 50 to 250 employees between the years 2017 and 2021. Before data collection, a pilot study was conducted with professors from two universities and managers from ten companies to validate the structured questioning. The final questionnaire resulting from the pilot is included in Appendix A. The data collection period lasted from June to July 2021. Before collecting the data, G*Power 3.1 was used to calculate the minimum sample size (Cunningham & McCrum-Gardner, 2007). The results of the a priori analysis using a Multiple Linear Regression setup show that for an effect size f2 of 0.15, a sample of 89 questionnaires is required. The total number of medium-sized companies that met the characteristics described above in the SABI database (https://sabi.bvdinfo.com) is 3465. From this population, 1,686 companies were randomly chosen, and a response was obtained from 310 experts, which involves a response rate of 18.38 %, with a factor of error of 5.76 % for p = q = 50 % and a level of reliability of 95.5 %. Table 1 indicates the respondents' demographic.

The independent samples *t*-test suggests no response bias since it revealed no significant differences between the first and last 155 responses regarding regenerative unlearning, collaboration with

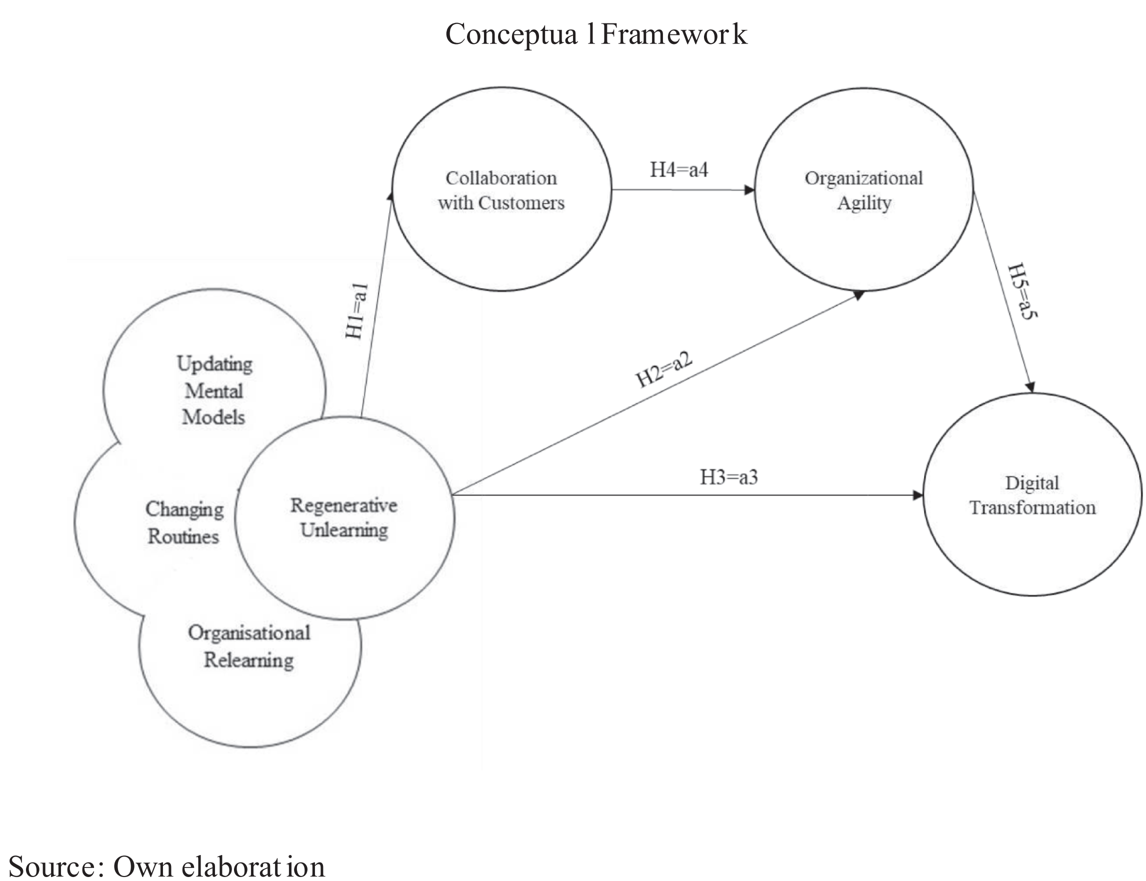

Fig. 1. Conceptual framework source: own elaboration.

Table 1
The respondents' demographic.

Gender	Male	Frequency=228	73.50%
	Female	Frequency=82	26.80%
Age	Min=24	Max=76	Average=45.36
Company size	Min=50	Max=249	Average=127.51
	Marketing & Sales	Frequency=14	4.50%
	Production	Frequency=114	36.80%
	Human Resources	Frequency=13	4.20%
Area	Research & Development	Frequency=76	24.50%
	Accounting & Finance	Frequency=7	2.30%
	Supply Chain Management	Frequency=18	5.80%
	Other	Frequency=68	21.90%

Source: Own elaboration.

customers, organisational agility, and digital transformation (p = 0.543, p = 0.735, p = 0.821 and p = 0.236, respectively). A solitary respondent was chosen from each company to participate in the survey, necessitating the consideration of potential common method variance (CMV) concerns (Podsakoff & Organ, 1986). Harmon's single-factor test was utilized to assess the likelihood of CMV. The Harman's Single Factor test was conducted in the current study using SPSS to confirm that no common method bias is present. As per the analysis, the first factor explained is 41.53 % which is below the threshold of 50 %, suggesting the absence of a CMV problem (Podsakoff, MacKenzie, & Podsakoff, 2012). For the higher robustness of this analysis, the measured latent marker variable (MLMV) approach was also used to detect potential problems of a post hoc common method variance (CMV), which is a method suggested for handling CMV in PLS-SEM models (Chin, Thatcher, Wright, & Steel, 2013). Considering that all the variables used in the model refer to the organisation level, the blue intention variable from an individual perspective operationalised with four items was used in the MLMV analysis (Miller & Simmering, 2022). Table 2 shows that the difference found in the R2 value in all endogenous variables is less than 10 % after removing the blue intention of the respondent, reflecting no single factor bias for most covariance (Chin et al., 2013; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

3.2. Measures

All constructs were measured using a 7-point Likert Scale, with all items ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). Nine items measured the company's regenerative unlearning. The items were adapted from Cegarra-Navarro and Wensley (2019) and Makkonen and Olkkonen (2017) and assessed the capability of a company to change routines, update mental models, and relearn over time while adapting to different environments. To measure collaboration with customers, the scale proposed by Heirati et al. (2016) was chosen. The scale consists of 3 items that refer to the company's effort to collaborate with customers. Organisational agility was measured using four items adapted from Srinivasan, Srivastava, and Iyer (2020) work. Finally, digital transformation was measured by asking whether the company focuses on digitising everything it can. Managers were also asked about the support

Table 2
Statistical remedy of Common Method Variance (CMV).

	Without including blue intention	Including blue intention
REU → ClC	0.320($R^2 = 0.103$)	0.319($R^2 = 0.103$)
REU → OA	0.353($R^2 = 0.325$)	0.353($R^2 = 0.329$)
REU → DT	0.394($R^2 = 0.290$)	0.394($R^2 = 0.290$)
ClC → OA	0.349($R^2 = 0.325$)	0.349($R^2 = 0.329$)
OA → DT	0.227($R^2 = 0.290$)	0.227($R^2 = 0.290$)

Source: Own elaboration.

from different business processes and about the amounts of data from various sources (Nasiri, Ukko, Saunila, & Rantala, 2020).

3.3. Assessment of the measures

We adopted PLS-SEM since we utilised composites estimated in Mode A. As shown in Table 3, the measures were evaluated using indicator loads, composite reliability, multicollinearity, and convergent and discriminant validity tests. Internal consistency reliability is usually the first criterion to be evaluated. The results shown in Table 3 indicate that the model satisfies all the essential criteria (Henseler et al., 2014). Following Hair, Hult, Ringle, Sarstedt, and Thiele (2017), Table 3 also displays the Variance Inflation Factors (VIFs) for all the variables, ranging from 1.768 to 3.863 and indicating the absence of collinearity issues.

To assess the discriminant validity, Fornell-Larcker and Heterotrait-Monotrait criteria were used. Table 4 shows that the AVE value is higher than the correlation coefficient between the competent and all the distinct variables for each latent variable. In addition, the threshold value of the HTMT is below 1 for all constructs, showing the discriminant validity of the constructs (Henseler et al., 2014).

4. Results

Following Sarstedt, Hair, Cheah, Becker, and Ringle (2019), regenerative unlearning was operationalised as a predictive second-order reflective-reflective construct using the two-stage approach. In the first stage, we got the score for changing routines, updating mental models, and relearning constructs without including the second-order construct in the model. The regenerative unlearning variable was measured with the first-stage scores in the second stage.

4.1. Measurement model

We assessed the significance of the path model relationships using bootstrapping analysis with 5,000 subsamples (bias-corrected and accelerated bootstrap, two-tailed test) in measurement and structural models following (Hair, Ringle, & Sarstedt, 2011). Table 5 shows that the internal consistency reliability and discriminant validity tests are statistically significant in the second-order constructs too. The fit indices of the saturated and estimated models were calculated to provide further robustness to the casualisation of the PLS-SEM analysis (Benitez, Henseler, Castillo, & Schuberth, 2020). The results show that both models had good fit indices (i.e. SRMR < 0.008; d_{ULS} and d_G below the 99 %-quantile of the bootstrap discrepancies (Hi_{95}) (Benitez et al., 2020).

4.2. Structural model

The analysis was conducted using Smart PLS version 4, employing the T-test with 5,000 subsamples to determine the significance level, path coefficients, and confidence intervals. As can be seen in Table 6, results show a positive relationship between regenerative unlearning and collaboration with customers, supporting hypothesis 1 ($a_1 = 0.320$, $p < 0.01$); regenerative unlearning and organisational agility, supporting hypothesis 2 ($a_2 = 0.353$, $p < 0.01$); and regenerative unlearning and digital transformation, supporting hypothesis 3 ($a_3 = 0.394$, $p < 0.01$). The findings also support hypothesis 4, showing that collaboration with customers positively influences organisational agility ($a_4 = 0.349$, $p < 0.01$). Finally, results support hypothesis 5, confirming the positive influence of organisational agility on digital transformation ($a_5 = 0.227$, $p < 0.01$). The findings displayed in Table 6 also show that neither of the two control variables was significant (Gender, $p = 0.914$ and Size, $p = 0.977$, respectively).

The cross-validated redundancy index (Q^2) in all cases is greater than zero ($Q^2_{ClC} = 0.08$; $Q^2_{OA} = 0.229$; and $Q^2_{DT} = 0.215$), which indicates that the structural model has a predictive capacity (Chin, 1998). Following

Table 3
Model estimates (first-order constructs).

		VIF	Weight	*t*-value	Loading	*t*-value	
UpMM	$UpMM_1$	1.768	0.376	11.782	0.844	38.354	AVE = 0.734
	$UpMM_2$	1.768	0.366	22.686	0.839	26.664	SCR = 0.892
	$UpMM_3$	2.000	0.424	20.139	0.887	46.959	α = 0.819
ChR	ChR_1	3.204	0.337	18.879	0.919	78.878	AVE = 0.858
	ChR_2	3.532	0.377	22.682	0.936	84.242	SCR = 0.948
	ChR_3	3.103	0.365	20.139	0.923	74.719	α = 0.917
REL	REL_1	2.918	0.354	23.361	0.913	66.693	AVE = 0.856
	REL_2	3.863	0.369	22.725	0.941	120.84	SCR = 0.947
	REL_3	3.200	0.358	22.759	0.921	78.804	α = 0.916
ClC	ClC_1	2.511	0.350	17.533	0.893	52.656	AVE = 0.818
	ClC_2	2.850	0.328	15.020	0.905	45.189	SCR = 0.931
	ClC_3	2.495	0.427	16.799	0.915	66.910	α = 0.889
OA	OA_1	2.159	0.285	16.560	0.834	31.027	AVE = 0.726
	OA_2	2.215	0.284	18.468	0.852	39.868	SCR = 0.914
	OA_3	2.196	0.314	15.171	0.851	39.274	α = 0.874
	OA_4	2.500	0.290	21.574	0.872	36.954	
DT	DT_1	2.364	0.307	17.338	0.873	50.409	AVE = 0.758
	DT_2	2.413	0.283	18.403	0.868	33.204	SCR = 0.914
	DT_3	2.693	0.277	18.155	0.884	51.620	α = 0.893
	DT_4	2.293	0.281	16.629	0.857	42.056	

Notes: Updating mental models → UpMM; Changing routines → ChR; Relearning → REL; Collaboration with Customers →(ClC); Organisational Agility→(OA); Digital Transformation→(DT); Variance inflation factor→ (VIF); Average variance extracted→ (AVE); Scale Composite Reliability→ (SCR); Cronbach's alpha→ (α).

Table 4
Discriminant validity analyses.

				Fornell-Larcker					
	Mean	S.D	HTMT	UpMM	ChR	REL	ClC	OA	DT
UpMM	4.873	1.213	0.736	***0.857***					
ChR	4.608	1.410	0.736	0.640	***0.926***				
REL	5.343	1.236	0.696	0.602	0.638	***0.925***			
ClC	5.543	1.280	0.516	0.200	0.312	0.311	***0.904***		
OA	5.598	0.984	0.516	0.365	0.384	0.426	0.461	***0.852***	
DT	5.446	1.265	0.530	0.406	0.406	0.480	0.309	0.410	***0.871***

Notes: Standard Desviation→(S.D); Heterotrait-monotrait ratio of correlations→(HTMT); Update mental models→ (UpMM); Change routines→ (ChR); Relearn→ (REL); Collaboration with Customers →(ClC); Organisational Agility→(OA); Digital Transformation→(DT); Diagonal values (square root of AVE are in bold) should be higher than off-diagonal correlations shown below the diagonal line.

Preacher and Hayes (2008), the confidence intervals of the indirect effects calculated through the post hoc analysis are significant since they do not contain zero values. These results support hypotheses H1, H2, H3, H4, and H5.

4.3. Endogeneity analysis

When using PLS-SEM is of crucial importance to address endogeneity issues. Endogeneity occurs when important variables are left out of the model, which can lead to inaccurate parameter estimations and question the validity of the findings (Antonakis et al., 2010). To avoid this, it is crucial to account for all variables to prevent endogeneity from becoming a serious issue. Our endogeneity test is based on the methodology of Hult et al. (2018) and involves several instrumental variables, including control variables such as gender and company size, in our model. We also use the Digital Transformation (DT) dependent variable and Gaussian copulas, as explained by Hult, Hair, and Jr., Proksch, D., Sarstedt, M., Pinkwart, A., & Ringle, C. M. (2018) and estimated by Park and Gupta (2012), to address endogeneity in the PLS-SEM context. To analyze endogeneity, we use two methods, which are illustrated below.

First, we check endogeneity in the variables of the study. Accordingly, we used two control variables associated with the dependent variable (i.e. DT). Upon conducting a 10.000-bootstrapping routine, we observed that the links for both control variables were non-significant (see Table 6). According to Sande and Ghosh (2018), the utilization of instrumental variables to address the endogeneity problem is a robust approach for estimating a model with three independent variables (REU, ClC, and OA) and one dependent variable (DT).

We also implemented the Gaussian copula procedure, following the demonstration outlined by Hult et al. (2018). In the first stage, we verified if the potentially endogenous variables were distributed abnormally. We did this by running the Cramer-van Mises test on the standardised composite scores of REU, ClC, OA, and DT (Becker, Datta, Lami, & Rouzé, 2021), which provided the PLS-SEM model estimation. The p-values ($p = 0.000$) for all our constructs indicated that none have normally distributed scores. In the second stage, we conducted a Gaussian copula analysis by including a copula for each independent variable with respect to the dependent variable. Consequently, we introduced three Gaussian copulas. However, none of these three copulas exhibit statistical significance. As a result of the analysis described above, there is no concern regarding endogeneity when estimating the

Table 5
Model estimates (second-order constructs).

Constructs		VIF	Loadings	Confidence intervals 2.5 %	97.5 %	
Regenerative Unlearning	UpMM	1.897	0.850	0.794	0.888	AVE = 0.751
	ChR	2.037	0.873	0.834	0.902	SCR = 0.900
	REL	1.895	0.876	0.834	0.904	HTMT = 0.575
Collaboration with Customers	ClC_1	2.511	0.891	0.852	0.920	AVE = 0.818
	ClC_2	2.850	0.904	0.849	0.936	SCR = 0.931
	ClC_3	2.495	0.917	0.886	0.937	HTMT = 0.516
Organisational Agility	OA_1	2.159	0.834	0.770	0.877	AVE = 0.726
	OA_2	2.215	0.851	0.806	0.888	SCR = 0.914
	OA_3	2.196	0.851	0.803	0.888	HTMT = 0.541
	OA_4	2.500	0.872	0.816	0.907	
Digital Transformation	DT_1	2.364	0.871	0.833	0.901	AVE = 0.758
	DT_2	2.413	0.868	0.808	0.907	SCR = 0.926
	DT_3	2.693	0.883	0.844	0.912	HTMT = 0.575
	DT_4	2.293	0.860	0.816	0.893	
	Estimated Model	Hi_{95}	Hi_{99}	Saturated Model	Hi_{95}	Hi_{99}
SRMR	0.038	0.042	0.048	0.035	0.038	0.043
d_{ULS}	0.154	0.189	0.244	0.130	0.154	0.191
d_G	0.158	0.161	0.297	0.157	0.167	0.316

Notes: The bold figures indicate the compliance level with the adjustment index.SRMR: Standardised Root Mean Square Residual, d_{ULS}: Unweighted Least Squares Discrepancy, d_G: Geodesic Discrepancy; Variance inflation factor→ (VIF); Average variance extracted→ (AVE); Scale Composite Reliability→ (SCR); Heterotrait-monotrait ratio of correlations→(HTMT).

Table 6
Structural model.

Hypotheses	Path coefficient	Confidence Intervals 2.5 %	97.5 %	(p-value)	R^2
H1: REU → ClC	$a_1 = 0.320$	0.200	0.446	0.000	0.103
H2: REU → OA	$a_2 = 0.353$	0.241	0.458	0.000	0.325
H3: REU → DT	$a_3 = 0.394$	0.266	0.524	0.000	0.290
H4: ClC → OA	$a_4 = 0.349$	0.233	0.463	0.000	0.325
H5: OA → DT	$a_5 = 0.227$	0.091	0.361	0.001	0.290
Gender → DT	$a_5 = -0.005$	−0.094	0.083	0.914	0.290
Size → DT	$a_5 = -0.001$	−0.097	0.092	0.977	0.290
Indirect effect		2.5 %	97.5 %	(p-value)	R^2
REU → ClC → OA	$a_1xa_2 = 0.112$	0.060	0.174	0.001	0.325
REU → ClC → OA → DT	$a_1xa_2xa_5 = 0.106$	0.042	0.178	0.005	0.290
ClC → OA → DT	$a_4xa_5 = 0.079$	0.027	0.147	0.037	0.290

Notes: Regenerative Unlearning→(REU); Collaboration with Customers →(ClC); Organisational Agility→(OA); Digital Transformation→(DT).

relationships within our proposed model.

5. Discussion and conclusions

5.1. Theoretical contributions

Digital transformation involves a fundamental change in mindset and how people approach their work. In this context, unlearning refers to the collective effort to set aside old habits, traditional ways of doing things, and outdated processes that are no longer effective or efficient in the digital age. From this point of view, unlearning is not an individual capacity (i.e. intentional unlearning) but a dynamic capability (i.e. regenerative unlearning). The results of the study help to understand how regenerative unlearning contributes to enhancing collaboration with customers, organisational agility, and digital transformation (RQ1) of medium-sized Spanish manufacturing companies. As Jones et al. (2021) discuss in their study, the main obstacles to digital transformation in manufacturing companies include a lack of employee skills and experience, an immature digital culture, and a lack of ability to properly interpret data. This shows the need for companies to be able to regenerate their employees' skills, routines, and organisational knowledge with the aim of adapting to digital change. This study demonstrates through a change of organisational routines, update of organisational mental models and increase of employees' competences, organisations can regenerate their knowledge structures to embrace change while increasing employees' skills.

Findings validate the positive relationship between regenerative unlearning and collaboration with customers, supporting H1. These results support Ortega-Gutiérrez et al. (2022) and Heirati et al. (2016) studies, which revealed that companies that unlearn improve their ability to collaborate with clients. Our findings contribute to the literature by acknowledging the noteworthiness of outer knowledge sources. In this regard, organisations may explore the external world for collaborative opportunities and then acquire external knowledge with a view to integrating it into their core processes. Unlearning old practices means shifting focus to a more end-user (customer)-centric approach, where new knowledge structures that replace outdated ones help companies understand and meet the changing needs of customers in the digital landscape. As a result, via the capitalisation of regenerative unlearning which covers the update of the mental models, the change of routines and the avoidance of defensive reasoning and the capacity of relearning (Cegarra-Navarro & Wensley, 2019; Makkonen & Olkkonen, 2017), companies may gain access to new ideas and promote substantive customer participation.

The results also validate the positive relationships between regenerative unlearning and organisational agility, supporting H2. These findings complement previous studies conducted by Cegarra-Navarro et al. (2016) and Zain et al. (2005) which approached the influence between knowledge renewal and organisational agility, simultaneously affirming the opportunity of knowledge regeneration through accommodating the existing acumen to new contextual challenges, as also explored by Pereira et al. (2019). The results show that digital transformation requires organisations to be agile to respond to market changes. This is why unlearning rigid structures and processes allows companies to adapt quickly to changing circumstances that favour digital integration. These results prove the relevance of challenging old mental models, changing routines, and relearning on the company's capability to respond effectively to emerging market situations, to seek and adopt new tools for meeting new needs, to foster flexible formal systems to engage with customers and to properly respond to emerging contexts. Indeed, by shedding outdated habits, routines, and knowledge, and adopting a mindset open to change, organisations become more receptive to novel ideas and innovative approaches. Regenerative unlearning therefore fosters flexibility, enabling organisations to adapt quickly to changing circumstances, avoid inertia and respond to new challenges derived from the environment.

Findings of the study also confirm the influence of regenerative unlearning on digital transformation, supporting H3. This study complements previous studies that proved the significant impact of the mental openness toward organisational change and development on technological disruption (Bordeleau & Felden, 2020; Cegarra-Navarro & Wensley, 2019; Willie & Nkomo, 2019). Specifically, this study demonstrates the role of regenerative unlearning as a strategic resource that enables organisations to have the updated multidimensional knowledge required in digital transformation processes. Results show that digital transformation is an ongoing process, as technology continues to advance. Under this framework, regenerative unlearning is part of a 'broader continuous learning process' with the adaptation and integration of new knowledge structures, which allows organisations to remain relevant and competitive. Regenerative unlearning is, therefore, crucial in digital transformation processes as it enables members of the organisation to unlearn obsolete technologies to adopt and integrate new digital tools and solutions. Moreover, since digital strategies require continuous re-evaluation (Matt et al., 2015), organisations that regenerate their knowledge structures will be better positioned to reassess their digital strategies thanks to their flexibility.

The findings of the study contribute to understanding the influence of collaboration with customers on organisational agility and the effect of organisational agility on the digital transformation of medium-sized Spanish manufacturing companies (RQ2). Particularly, results support H4, revealing the positive influence of collaboration with customers on organisational agility. These empirical results support previous findings according to which companies can improve their organisational agility through a network with external partner (García-Murillo & Annabi, 2002; Mehdibeigi et al., 2016) and customer experiences (Mihardjo et al., 2019). Our results contribute to these studies showing that collaboration with customers improves organisational agility by providing information and feedback, allowing the organisation to understand its customers' changing needs, responding quickly to market changes, and creating an adaptive customer-centric culture. In other words, collaboration with customers allow firms to build solid networks with customers to better search and integrate new knowledge sources.

Finally, results of the study show the positive influence of organisational agility on digital transformation, supporting H5. The findings validate earlier research that organisational agility drives digital transformation (McDermott et al., 2022; Shakina et al., 2021). Given that digital transformation typically involves a wide spectrum of knowledge activities, such as design thinking to analyse and optimise the customer journey or implementing automated customer service, the agility required to adapt to technological developments may help organisations deliver timely knowledge that is valuable and validated. Organisational agility tailors proactive change paths, implicitly paving the way for digital transformation to unfold and supporting the adaptability necessary to respond to rapid disruptions in the digital marketplace.

5.2. Managerial implications

The adoption of digital technologies by businesses and organisations over the past few decades has been compelled by the need to primarily modify mental models alongside business models (Cubillas-Para et al., 2023). The above discussion suggests that regenerating knowledge, routines, and behaviours is crucial to collaborate with customers, improve agility and embrace digital transformation initiatives. To achieve regenerated knowledge structures in the organisation, managers can promote unlearning in the company by recognising the need to unlearn, fostering a growth mindset, challenging assumptions, and creating a space where ideas can be exchanged (Cegarra-Navarro & Wensley, 2019). In this sense, they must foster a culture of continuous learning and growth within the organisation. Additionally, the organisation must allocate resources to increase employees' digital skills, as these may be specific and may not currently exist in the market (Cirillo, Fanti, Mina, & Ricci, 2023). For example, by allocating part of the budget to specific training courses on digital transformation technologies such as the Internet of Things, AI, cloud computing or machine learning.

Another potential action that organisations can undertake is the creation of cross-functional teams (Gimpel et al., 2018). Cross-functional teams bring together people with diverse skills and experience that can be more responsive to the changing needs of the market (Ambrose, Matthews, & Rutherford, 2018). In this way, employees can collaborate in dealing with the dynamism of the environment. Through this strategic approach, organisations can improve their agility and adaptability. Organisations can also create cross-department collaboration to facilitate the learning processes of all employees, who can learn from other mistakes and be aware of the new needs.

The results also highlight the importance of customer collaboration in improving organisational agility in the context of digital transformation of manufacturing companies. Firms must ensure that they interact with customers, recognising their contribution for ideas and collaboration, as well as their knowledge (Morgan & Anokhin, 2023). In this regard, to strengthen customer collaboration, companies can seek feedback from customers on the effectiveness of new applications that have been developed. They can also collaborate with them in the development of digital solutions that address their specific needs, as well as in the creation of new customer-focused digital services.

5.3. Limitations and future research

The current study acknowledges multiple limitations that could guide future research lines and provides recommendations for subsequent research. Firstly, this study has a quantitative nature. Future research should include relevant qualitative factors for a more comprehensive understanding of the theme under analysis. For instance, in-depth interviews with a significant sample of CEOs may contribute positively to extrapolating and complementing the results with absolute reliability. Through the analysis of these interviews, it will be possible to analyse specific problems encountered by medium-sized Spanish manufacturing companies when embracing digital transformation to develop digital strategies more tailored to this sample. This study has also analysed a sample of Spanish medium-sized manufacturing companies. The extension of the research on companies coming from different countries would enrich the theoretical and organisational insights by supporting or not the validity of the model. Moreover, given that digital transformation is multifaceted, empirically evaluating the advanced model with samples from large companies would round off the analytical framework.

Like any survey research, this study has limitations which provide avenues for future research. First, the empirical findings are based on cross-sectional data, which makes it impossible to assess changes over time. Second, it should be noted that we considered only one data source as we have tried to make the survey anonymous and to motivate the participation of the sample. In this regard, multiple data sources may be considered in future research. Third, despite controlling common method variance using different analyses, it may not be completely ruled out. Therefore, future studies should examine other organizations and other control variables that help to improve inferences about statistical relationships in data (such as hierarchical levels, type of ownership or level of studies of the manager).

6. AI Statement

During the preparation of this work, the authors used Grammarly in order to improve the grammar as none of the authors are English native. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Clara Cubillas-Para: Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Conceptualization. **Juan Gabriel Cegarra-Navarro:** Writing – review & editing, Writing – original draft, Validation, Software, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Elena-Mădălina Vătămănescu:** Writing – review & editing, Visualization, Supervision, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors acknowledge the Spanish Ministry of Universities for supporting this work [FPU20/05986].

Funding information

This work was supported by *Ministerio de Universidades, Gobierno de España (Ministry of Universities, Spanish Government)* [FPU20/05986].

Appendix A

Questionnaire items

Please rate the following statements from 1 (total disagreement) to 7 (complete agreement).
Unlearning (Changing routines + Leveraging + Relearning)
Updating mental models
$UpMM_1$: Employees are more willing to adopt new work methods than competitors.
$UpMM_2$: Employees have room to exploit new opportunities.
$UpMM_3$: Employees are encouraged to promote new visions, goals, and ideas.
Changing routines and avoiding defensive reasoning
ChR_1: New routines enable the active participation of employees in generating ideas for new products or services.
ChR_2: New routines enable the active participation of employees in generating ideas for new production processes or organisational procedures.
ChR_3: New routines systematise employee experiences.
Relearning
REL_1: The company emphasises the need to increase employees' competence level.
REL_2: The company allocates resources to increase employee competence.
REL_3: The company encourages employees to learn from their experiences.
Source: Adapted from Cegarra-Navarro and Wensley (2019); Makkonen and Olkkonen (2017)
Collaboration with Customers
ClC_1: Helping customers define product/service specifications.
ClC_2: Jointly develop the product or service.
ClC_3: Improving the efficiency of the product or service.
Source: Heirati et al. (2016)
Organisational Agility
OA_1: Responding effectively to emerging market situations (routine or unforeseen) quickly.
OA_2: Seeking and adopting structures to deal with unpredictable market situations.
OA_3: Having flexible formal systems to meet commitments with customers.
OA_4: Effectively responds to emerging contexts of various products and services.
Source: Srinivasan et al. (2020)
Digital transformation
DT_1: Digitising everything you can.
DT_2: Collect large amounts of data from different sources.
DT_3: Creating a network between different business processes with digital technologies.
DT_4: Improving an efficient customer interface with digitisation.
Source: Nasiri et al. (2020)

References

Ambrose, S. C., Matthews, L. M., & Rutherford, B. N. (2018). Cross-functional teams and social identity theory: A study of sales and operations planning. *Journal of Business Research, 92*, 270–278. https://doi.org/10.1016/j.jbusres.2018.07.052

Becker, S., Datta, N., Lami, L., & Rouzé, C. (2021). Energy-constrained discrimination of unitaries, quantum speed limits, and a Gaussian Solovay-Kitaev theorem. *Physical Review Letters, 126*(19), Article 190504. https://doi.org/10.1103/PhysRevLett.126.190504

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information and Management, 57*(2), Article 103168. https://doi.org/10.1016/j.im.2019.05.003

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Digital business strategy: Toward a next generation of insights. *MIS Quarterly, 37*(2), 471–482. https://doi.org/10.25300/MISQ/2013/37:2.3

Bican, P. M., & Brem, A. (2020). Digital business model, digital transformation, digital entrepreneurship: Is there a sustainable "digital"? *Sustainability (Switzerland), 12* (13). https://doi.org/10.3390/su12135239

Bordeleau, F. È., & Felden, C. (2020). Digitally transforming organisations: A review of change models of industry 4.0. *27th European Conference on Information Systems - Information Systems for a Sharing Society, ECIS 2019*.

Broccardo, L., Zicari, A., Jabeen, F., & Bhatti, Z. A. (2023). How digitalization supports a sustainable business model: A literature review. *Technological Forecasting and Social Change, 187*, Article 122146. https://doi.org/10.1016/j.techfore.2022.122146

Caputo, A., Pizzi, S., Pellegrini, M. M., & Dabić, M. (2021). Digitalization and business models: Where are we going? a science map of the field. *Journal of Business Research, 123*, 489–501. https://doi.org/10.1016/j.jbusres.2020.09.053

Çebi, A., Özdemir, T. B., Reisoğlu, İ., & Çolak, C. (2022). From digital competences to technology integration: Re-formation of pre-service teachers' knowledge and understanding. *International Journal of Educational Research, 113*, Article 101965. https://doi.org/10.1016/j.ijer.2022.101965

Cegarra-Navarro, J. G., & Wensley, A. (2019). Promoting intentional unlearning through an unlearning cycle. *Journal of Organizational Change Management, 32*(1), 67–79. https://doi.org/10.1108/JOCM-04-2018-0107

Cegarra-Navarro, J.-G., Soto-Acosta, P., & Wensley, A. K. P. (2016). Structured knowledge processes and firm performance: The role of organizational agility. *Journal of Business Research, 69*(5), 1544–1549. https://doi.org/10.1016/j.jbusres.2015.10.014

Cegarra-Navarro, J.-G., Wensley, A., Batistic, S., Evans, M., & Cubillas-Para, C. (2021). Minimizing the effects of defensive routines on knowledge hiding though unlearning. *Journal of Business Research, 137*, 58–68. https://doi.org/10.1016/j.jbusres.2021.08.021

Chan, E. S. W., Okumus, F., & Chan, W. (2015). Barriers to environmental technology adoption in hotels. *Journal of Hospitality & Tourism Research, 42*(5), 829–852. https://doi.org/10.1177/1096348015614959

Chin, W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research, 295*(2), 295–336. https://doi.org/10.1016/j.aap.2008.12.010

Chin, W. W., Thatcher, J. B., Wright, R. T., & Steel, D. (2013). Controlling for Common Method Variance in PLS Analysis: The Measured Latent Marker Variable Approach. In H. Abdi, W. W. Chin, V. Esposito Vinzi, G. Russolillo, & L. Trinchera (Eds.), *Springer Proceedings in Mathematics and Statistics* (Vol. 56, pp. 231–239). Springer. DOI: 10.1007/978-1-4614-8283-3_16.

Cirillo, V., Fanti, L., Mina, A., & Ricci, A. (2023). The adoption of digital technologies: Investment, skills, work organisation. *Structural Change and Economic Dynamics, 66*, 89–105. https://doi.org/10.1016/j.strueco.2023.04.011

Çıdık, M. S., Boyd, D., & Thurairajah, N. (2017). Ordering in disguise: Digital integration in built-environment practices. *Building Research & Information, 45*(6), 665–680. https://doi.org/10.1080/09613218.2017.1309767

Cubillas-Para, C., Cegarra-Navarro, J. G., & Wensley, A. (2023). Unlearning as a Future Challenge for Knowledge Management. In C. Bratinau, M. Handzic, & Bolisani E (Eds.), *The Future of Knowledge Management. Knowledge Management and Organizational Learning* (Vol. 12, pp. 149–168). Springer. DOI: 10.1007/978-3-031-38696-1_8.

Cunningham, J. B., & McCrum-Gardner, E. (2007). Power, effect and sample size using GPower: Practical issues for researchers and members of research ethics committees. *Evidence Based Midwifery, 5*, 132–136.

Echajari, L., & Thomas, C. (2015). Learning from complex and heterogeneous experiences: The role of knowledge codification. *Journal of Knowledge Management, 19*(5), 968–986. https://doi.org/10.1108/JKM-02-2015-0048

Fahey, R. A., & Hino, A. (2020). COVID-19, digital privacy, and the social limits on data-focused public health responses. *International Journal of Information Management, 55*, Article 102181. https://doi.org/10.1016/j.ijinfomgt.2020.102181

Feliciano-Cestero, M. M., Ameen, N., Kotabe, M., Paul, J., & Signoret, M. (2023). Is digital transformation threatened? a systematic literature review of the factors influencing firms' digital transformation and internationalization. *Journal of Business Research, 157*, Article 113546. https://doi.org/10.1016/j.jbusres.2022.113546

Fenech, R., Baguant, P., & Ivanov, D. (2019). The changing role of human resource management in an era of digital transformation. *Journal of Management Information and Decision Science, 22*(2), 176–180.

Filieri, R. (2010). *Overcoming knowledge sharing barriers through communities of practice*. Cambridge Scholars Publishing.

García-Murillo, M., & Annabi, H. (2002). Customer knowledge management. *Journal of the Operational Research Society, 53*(8), 875–884. https://doi.org/10.1057/palgrave.jors.2601365

Garcia-Perez, A., Cegarra-Navarro, J. G., Sallos, M. P., Martinez-Caro, E., & Chinnaswamy, A. (2022). Resilience in healthcare systems: Cyber security and digital transformation. *Technovation, 102583*. https://doi.org/10.1016/j.technovation.2022.102583

Gimpel, H., Hosseini, S., Huber, R. X., Probst, L., Röglinger, M., & Faisst, U. (2018). Structuring digital transformation: A framework of action fields and its application at ZEISS. *Journal of Information Technology Theory and Application, 19*(3), 31–54.

Gimpel, H., & Röglinger, M. (2015). *Digital Transformation: Changes and Chances - Insights based on an empirical study*. https://www.fim-rc.de/Paperbibliothek/Veroeffentlicht/542/wi-542.pdf.

Guo, R., Yin, H., & Liu, X. (2023). Coopetition, organizational agility, and innovation performance in digital new ventures. *Industrial Marketing Management, 111*, 143–157. https://doi.org/10.1016/j.indmarman.2023.04.003

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., & Thiele, K. O. (2017). Mirror, mirror on the wall: A comparative evaluation of composite-based structural equation modeling methods. *Journal of the Academy of Marketing Science, 45*(5), 616–632. https://doi.org/10.1007/s11747-017-0517-x

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *The Journal of Marketing Theory and Practice, 19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hamid, A. (2022). Managing digital integration routines in engineering firms: Cases of disruptive BIM cloud collaboration protocols. *Journal of Management in Engineering, 38*(1), 5021012. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000988

Heirati, N., O'Cass, A., Schoefer, K., & Siahtiri, V. (2016). Do professional service firms benefit from customer and supplier collaborations in competitive, turbulent environments? *Industrial Marketing Management, 55*, 50–58. https://doi.org/10.1016/j.indmarman.2016.02.011

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., Ketchen, D. J., Hair, J. F., Hult, G. T. M., & Calantone, R. J. (2014). Common beliefs and reality about PLS. *Organizational Research Methods, 17*(2), 182–209. https://doi.org/10.1177/1094428114526928

Hult, G. T. M., Hair, J. F., & Jr., Proksch, D., Sarstedt, M., Pinkwart, A., & Ringle, C. M.. (2018). Addressing endogeneity in international marketing applications of partial least squares structural equation modeling. *Journal of International Marketing, 26*(3), 1–21. https://doi.org/10.1509/jim.17.0151

Jones, M. D., Hutcheson, S., & Camba, J. D. (2021). Past, present, and future barriers to digital transformation in manufacturing: A review. *Journal of Manufacturing Systems, 60*, 936–948. https://doi.org/10.1016/j.jmsy.2021.03.006

Kane, G. C., Palmer, D., Nguyen, A. P., Kiron, D., & Buckley, N. (2015). Strategy, not technology, drives digital transformation. *MIT Sloan Management Review & Deloitte, 27*, 57181. http://sloanreview.mit.edu/projects/strategy-drives-digital-transformation/.

Kindermann, B., Schmidt, C. V. H., Burger, O., & Flatten, T. C. (2022). Why teams matter in customer involvement – The moderating effects of team social cohesion and team autonomy. *Journal of Business Research, 146*, 70–83. https://doi.org/10.1016/j.jbusres.2022.03.060

Li, S., Gao, L., Han, C., Gupta, B., Alhalabi, W., & Almakdi, S. (2023). Exploring the effect of digital transformation on firms' innovation performance. *Journal of Innovation & Knowledge, 8*(1), Article 100317. https://doi.org/10.1016/j.jik.2023.100317

Makkonen, H., & Olkkonen, R. (2017). Interactive value formation in interorganizational relationships: Dynamic interchange between value co-creation, no-creation, and co-destruction. *Marketing Theory, 17*(4), 517–535. https://doi.org/10.1177/1470593117699661

Matt, C., Hess, T., & Benlian, A. (2015). Digital transformation strategies. *Business & Information Systems Engineering, 57*(5), 339–343. https://doi.org/10.1007/s12599-015-0401-5

Mattila, M., Yrjölä, M., & Hautamäki, P. (2021). Digital transformation of business-to-business sales: What needs to be unlearned? *Journal of Personal Selling & Sales Management, 41*(2), 113–129. https://doi.org/10.1080/08853134.2021.1916396

McDermott, O., Foley, I., Antony, J., Sony, M., & Butler, M. (2022). The impact of industry 4.0 on the medical device regulatory product life cycle compliance. *Sustainability, 14*(21). https://doi.org/10.3390/su142114650

McDermott, R., & O'Dell, C. (2001). Overcoming cultural barriers to sharing knowledge. *Journal of Knowledge Management, 5*(1), 76–85. https://doi.org/10.1108/13673270110384428

McEvily, B., & Marcus, A. (2005). Embedded ties and the acquisition of competitive capabilities. *Strategic Management Journal, 26*(11), 1033–1055. https://doi.org/10.1002/smj.484

Mehdibeigi, N., Dehghani, M., & Yaghoubi, N. M. (2016). Customer knowledge management and organization's effectiveness: Explaining the mediator role of organizational agility. *Procedia - Social and Behavioral Sciences, 230*, 94–103. https://doi.org/10.1016/j.sbspro.2016.09.012

Mihardjo, L. W., Sasmoko, S., Alamsjah, F., & Djap, E. (2019). Towards co-creation strategy and organizational agility based on customer experience orientation to shape transformational performance. *International Journal of Innovation, Creativity and Change, 6*(1), 236–248.

Miller, B. K., & Simmering, M. J. (2022). Attitude toward the color blue: An ideal marker variable. *Organizational Research Methods*. https://doi.org/10.1177/10944281221075361

Morgan, T., & Anokhin, S. (2023). Entrepreneurial orientation and new product performance in SMEs: The mediating role of customer participation. *Journal of Business Research, 164*, Article 113921. https://doi.org/10.1016/j.jbusres.2023.113921

Najafi-Tavani, S., Zaefarian, G., Robson, M. J., Naudé, P., & Abbasi, F. (2022). When customer involvement hinders/promotes product innovation performance: The concurrent effect of relationship quality and role ambiguity. *Journal of Business Research, 145*, 130–143. https://doi.org/10.1016/j.jbusres.2022.03.001

Nasiri, M., Ukko, J., Saunila, M., & Rantala, T. (2020). Managing the digital supply chain: The role of smart technologies. *Technovation, 96–97*, Article 102121. https://doi.org/10.1016/j.technovation.2020.102121

Niewohner, N., Asmar, L., Wortmann, F., Roltgen, D., Kuhn, A., & Dumitrescu, R. (2019). Design fields of agile innovation management in small and medium sized enterprises. *Procedia CIRP, 84*, 826–831.

Ortega-Gutiérrez, J., Cepeda-Carrión, I., & Alves, H. (2022). The role of absorptive capacity and organizational unlearning in the link between social media and service dominant orientation. *Journal of Knowledge Management, 26*(4), 920–942. https://doi.org/10.1108/JKM-06-2020-0487

Pereira, V., Mellahi, K., Temouri, Y., Patnaik, S., & Roohanifar, M. (2019). Investigating dynamic capabilities, agility and knowledge management within EMNEs-longitudinal evidence from Europe. *Journal of Knowledge Management, 23*(9), 1708–1728. https://doi.org/10.1108/JKM-06-2018-0391

Pavlou, P. A., & El Sawy, O. A. (2011). Understanding the elusive black box of dynamic capabilities. *Decision Sciences, 42*(1), 239–273. https://doi.org/10.1111/j.1540-5915.2010.00287.x

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology, 63*, 539–569. https://doi.org/10.1146/annurev-psych-120710-100452

Podsakoff, P. M., & Organ, D. W. (1986). Self-reports in organizational research: Problems and prospects. *Journal of Management, 12*(4), 531–544. https://doi.org/10.1177/014920638601200408

Preacher, K. J., & Hayes, A. F. (2008). *Asymptotic and Resampling Strategies for Assessing and Comparing Indirect Effects in Multiple Mediator Models*. *40*(3), 879–891. DOI: 10.3758/BRM.40.3.879.

Sande, J. B., & Ghosh, M. (2018). Endogeneity in survey research. *International Journal of Research in Marketing, 35*(2), 185–204. https://doi.org/10.1016/j.ijresmar.2018.01.005

Sarstedt, M., Hair, J. F., Cheah, J.-H., Becker, J.-M., & Ringle, C. M. (2019). How to specify, estimate, and validate higher-order constructs in PLS-SEM. *Australasian Marketing Journal (AMJ), 27*(3), 197–211. https://doi.org/10.1016/j.ausmj.2019.05.003

Shakina, E., Parshakov, P., & Alsufiev, A. (2021). Rethinking the corporate digital divide: The complementarity of technologies and the demand for digital skills. *Technological Forecasting and Social Change, 162*, Article 120405. https://doi.org/10.1016/j.techfore.2020.120405

Srinivasan, M., Srivastava, P., & Iyer, K. N. S. (2020). Response strategy to environment context factors using a lean and agile approach: Implications for firm performance. *European Management Journal, 38*(6), 900–913. https://doi.org/10.1016/j.emj.2020.04.003

Statsenko, L., & Corral de Zubielqui, G. (2020). Customer collaboration, service firms' diversification and innovation performance. *Industrial Marketing Management, 85*, 180–196. https://doi.org/10.1016/j.indmarman.2019.09.013

Tanushree, Sahoo, C. K., & Chaubey, A. (2023). Evolution of organizational agility research: A retrospective view. *Benchmarking: An International Journal, ahead-of-print (ahead-of-print)*. https://doi.org/10.1108/BIJ-02-2023-0086

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal, 28*(13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D., & Pisano, G. (1994). The dynamic capabilities of firms: An introduction. *Industrial and Corporate Change, 3*(3), 537–556. https://doi.org/10.1093/icc/3.3.537-a

Tsai, F.-S. (2018). Knowledge heterogeneity, social capital, and organizational innovation. *Journal of Organizational Change Management, 31*(2), 304–322. https://doi.org/10.1108/JOCM-03-2017-0047

Vătămănescu, E.-M., Andrei, A. G., Gazzola, P., & Dominici, G. (2018). Online academic networks as knowledge brokers: The mediating role of organizational support. *Systems, 6*(2), 11. https://doi.org/10.3390/systems6020011

Vătămănescu, E.-M., Cegarra-Navarro, J.-G., Andrei, A. G., Dincă, V.-M., & Alexandru, V.-A. (2020). SMEs strategic networks and innovative performance: A relational design and methodology for knowledge sharing. *Journal of Knowledge Management, 24*(6), 1369–1392. https://doi.org/10.1108/JKM-01-2020-0010

Vătămănescu, E.-M., Cegarra-Navarro, J.-G., Martínez-Martínez, A., Dincă, V.-M., & Dabija, D.-C. (2023). Revisiting online academic networks within the COVID-19 pandemic – From the intellectual capital of knowledge networks towards institutional knowledge capitalization. *Journal of Intellectual Capital, 24*(4), 948–973. https://doi.org/10.1108/JIC-01-2022-0027

Vătămănescu, E.-M., Bratianu, C., Dabija, D.-C., & Popa, S. (2023). Capitalizing online knowledge networks: From individual knowledge acquisition towards organizational achievements. *Journal of Knowledge Management, 27*(5), 1366–1389. https://doi.org/10.1108/JKM-04-2022-0273

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research, 122*, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems, 28*(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

Vuchkovski, D., Zalaznik, M., Mitręga, M., & Pfajfar, G. (2023). A look at the future of work: The digital transformation of teams from conventional to virtual. *Journal of Business Research, 163*, Article 113912. https://doi.org/10.1016/j.jbusres.2023.113912

Walter, A.-T. (2021). Organizational agility: Ill-defined and somewhat confusing? A systematic literature review and conceptualization. *Management Review Quarterly, 71* (2), 343–391. https://doi.org/10.1007/s11301-020-00186-6

Wang, X., Liu, Z., Li, J., & Lei, X. (2023). How organizational unlearning leverages digital process innovation to improve performance: The moderating effects of smart technologies and environmental turbulence. *Technology in Society, 75*, Article 102395. https://doi.org/10.1016/j.techsoc.2023.102395

Willie, M. M., & Nkomo, P. (2019). Digital transformation in healthcare-South Africa context. *Global Journal of Immunology and Allergic Diseases, 7*, 1–5.

Winby, S., & Worley, C. G. (2014). Management processes for agility, speed, and innovation. *Organizational Dynamics, 43*(3), 225–234. https://doi.org/10.1016/j.orgdyn.2014.08.009

Yang, J., & Wang, F.-K. (2017). Impact of social network heterogeneity and knowledge heterogeneity on the innovation performance of new ventures. *Information Discovery and Delivery, 45*(1), 36–44. https://doi.org/10.1108/IDD-11-2016-0038

Zain, M., Rose, R. C., Abdullah, I., & Masrom, M. (2005). The relationship between information technology acceptance and organizational agility in Malaysia. *Information and Management, 42*(6), 829–839. https://doi.org/10.1016/j.im.2004.09.001

Zhao, Y., Lu, Y., & Wang, X. (2013). Organizational unlearning and organizational relearning: A dynamic process of knowledge management. *Journal of Knowledge Management, 17*(6), 902–912. https://doi.org/10.1108/JKM-06-2013-0242

Zheng, S., Zhang, W., & Du, J. (2011). Knowledge-based dynamic capabilities and innovation in networked environments. *Journal of Knowledge Management, 15*(6), 1035–1051. https://doi.org/10.1108/13673271111179352

Clara Cubillas-Para is a PhD student in the Inter-university program in Economics, Business and Legal Sciences of the Technical University of Cartagena, Cartagena, Spain. Currently, she is working as a pre-doctoral researcher at this university with a contract funded by the Ministry of Universities of the Spanish Government in the Department of Business Economics within the areas of business organisation and marketing. Her research interests include knowledge management, consumer behaviour, innovation adoption processes, and the tourism industry.

Juan Gabriel Cegarra-Navarro received the Ph.D. degree in management from the Universidad Nacional de Educación a Distancia (UNED) of Madrid, Spain, in 2002. He is currently a Full Professor with the Technical University of Cartagena, Cartagena, Spain. He also serves as an Associate Editor and Regional Editorial for several flagship journals, including Knowledge and Process Management and Journal of Knowledge Management. His research interests include knowledge management, technology transfer, innovation, and technology management.